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Research on the Mathematical Model of Fairness of Educational Resources

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Abstract: The equitable distribution of educational resources has become a key focus in global education development. While advanced technologies such as artificial intelligence provide tools for data analysis and decision-making, their integration into educational planning raises challenges in fairness assessment. This paper aims to address the limitations of traditional evaluation methods by proposing a quantitative model that captures the complexity and heterogeneity of educational ecosystems. A multi-dimensional framework is introduced, supported by optimization algorithms and fairness indicators, to enhance the transparency and effectiveness of educational resource allocation.

Keywords: educational resources; fairness; research on mathematical models

1. Introduction

The inequality in resource distribution remains a key challenge in achieving fairness in global education, highlighting the need to address disparities that may arise during the pursuit of educational advancement. Traditional evaluation methods often rely on a single economic indicator, with limited consideration of critical aspects in the educational production process, such as the deployment structure of teaching staff, the quality of digital hardware environments, and the standards of course delivery. Consequently, the outcomes of policy interventions often fail to meet expectations. The current emerging quantitative models provide apparent limitations in the ingredients of the increasingly dynamic regional differences as described above. Furthermore, the static weight allocation process in knowing educational production institution structure and investment cannot translate to the complexity of the spatio-temporal heterogeneity of the educational ecosystem. In this study we focus on these pain points and develop a 3D index system that includes hardware investment, software strength and development potential, in addition to re-establishing the calculation dimension of the Gini coefficient for heightened cross-regional comparability. Then we create a multi-objective optimization framework that integrates the policy constraints and aspects of education as a real variable, and a deep reinforcement learning algorithm model to simulate the game process of a resource allocation process to create a dynamic situational decision-making schema as it relates to efficiency consideration and also fairness. The experimental design focuses on verifying the explanatory power and prediction accuracy of the model in real educational scenarios, revealing the differentiated effects of different intervention paths on the fairness index, and providing an innovative methodology for solving the problem of misallocation of educational resources.

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2. Quantitative Model of Educational Resource Fairness

2.1. Construction of the Index System

The quantification of the fairness of educational resources requires the construction of a multi-dimensional evaluation system, with a focus on three core dimensions: spatial balance, group coverage, and resource adequacy. Spatial equilibrium measures the differences in resource allocation between counties or schools, and adopts the improved Gini coefficient to eliminate the defect of traditional algorithms being sensitive to extreme values [1]. Define the total amount of educational resources as R, and the distribution sequence of resources within counties or between schools as $\{r_1, r_2, ..., r_n\}$, the optimization formula of the Gini coefficient is (1):

$$G = \frac{1}{2n^2\mu}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|r_i - r_j\right| \cdot w_{ij} \tag{1}$$

Among them, μ is the mean value of resources, and w_{ij} is the dynamic weight matrix based on geographical distance or population density to enhance regional comparability. Group coverage focuses on the proportion of resource acquisition for vulnerable groups such as migrant children and students with disabilities, and constructs the coverage index C as shown in Formula (2):

$$C = 1 - \sqrt{\sum_{k=1}^{m}\alpha_k\left(\frac{E_k - A_k}{E_k}\right)^2} \tag{2}$$

In the formula, E_k represents the theoretical proportion of resources that the KTH type of group should enjoy, A_k represents the actual proportion, and α_k represents the group weight determined by the entropy weight method, reflecting the differences in policy priorities [2].

The compliance levels of basic indicators such as per-student funding and teacher-student ratio were evaluated for resource adequacy, using standardized thresholds and linear weighted models. Define the per-student funding adequacy S_f and the student-teacher ratio adequacy S_t, as shown in Formula (3):

$$S_f = \frac{F_{actual}}{F_{standard}}, S_t = \frac{T_{actual}}{T_{standard}} \tag{3}$$

Among them, $F_{standard}$ and $T_{standard}$ represent the national or regional education standard values. The comprehensive sufficiency Index A is synthesized by weighting the indicators as shown in Formula (4):

$$A = \beta_1 S_f + \beta_2 S_t \tag{4}$$

The weight coefficient β is determined through dual verification of principal component analysis and expert scoring method to ensure the reliability and validity of the index. This system provides a structured analysis framework for accurately diagnosing the bottlenecks of educational equity through the deconstruction of spatial differences, the characterization of group heterogeneity and the control of resource bottom lines [3].

2.2. Comprehensive Index Calculation Model (ERF Index)

2.2.1. Improvement of the Gini Coefficient

The traditional Gini coefficient has significant limitations in the analysis of the spatial balance of educational resources. Its symmetry assumption and linear ranking rules are difficult to accurately describe the non-uniform distribution characteristics of differences within counties or between schools. To address this issue, a multi-dimensional weight correction mechanism is introduced to reconstruct the Gini coefficient algorithm. The educational resource allocation sequence $X = \{x_1, x_2, \ldots, x_n\}X = \backslash\{x_1, x_2, \ldots, x_n\backslash\}X = \{x_1, x_2, \ldots, x_n\}$ corresponds to the population proportion sequence of each geographical unit $P = \{p_1, p_2, \ldots, p_n\}P = \backslash\{p_1, p_2, \ldots, p_n\backslash\}P = \{p_1, p_2, \ldots, p_n\}$. The improved calculation model of the Gini coefficient $G'G'G'$ is shown in Formula (5):

$$G' = \frac{\sum_{i=1}^{n} p_i p_j |x_i - x_j|}{2\bar{X}\sum_{i=1}^{n} {p_i}^2} \tag{5}$$

Among them, $\bar{X}$ is the average per capita possession of educational resources. The weight pipj is embedded in the influence of population distribution differences on fairness to eliminate the bias caused by the traditional algorithm ignoring regional scale heterogeneity. This model converts the area comparison of the Lorentz curve into a dynamic weighted distance measure, making the calculation results more in line with the policy logic of "on-demand allocation" of educational resources [4].

The improved Gini coefficient, as the core component of the ERF index, needs to be standardized and coupled with the indicators of group coverage and resource adequacy. After eliminating the dimensional differences by using the range method, the weights $\omega_1, \omega_2, \omega_3$ of each dimension are determined by the entropy weight method, and the comprehensive index is constructed as shown in Formula (6):

$$ERF = \omega_1(1 - G') + \omega_2 C + \omega_3 A \quad (6)$$

In the formula, C represents the group coverage index and A represents the resource adequacy index. Improve the Gini coefficient to capture the matching efficiency of resource distribution and population density in the spatial dimension, avoid the underestimation risk of weak areas by a single economic indicator, and provide a robust quantitative benchmark for cross-regional fairness comparisons. This model enhances the targeting of policy intervention by decoupling the scale effect and structural effect of resource allocation.

2.2.2. Synthesis of Comprehensive Index

The synthesis of the comprehensive index requires overcoming technical bottlenecks in the standardization of multi-dimensional indicators and the allocation of weights to achieve coordinated optimization of indicators including spatial balance, group coverage, and resource adequacy. To improve the Gini coefficient G', the population coverage index C and the resource adequacy index A, due to the differences in dimension and order of magnitude, the Z-score standardization method needs to be adopted to eliminate the distribution shift if (7):

$$X_k' = \frac{X_k - \mu}{\sigma} \quad (7)$$

Among them, μ is the mean value of the index, σ is the standard deviation. After standardization, each index is rescaled to have a mean of 0 and a standard deviation of 1, allowing for comparison across different units even if the original data does not follow a normal distribution. The construction of the ERF index adopts a nonlinear addition-multiplication hybrid model to enhance the characterization ability of the interaction effect of the index, such as Formula (8):

$$ERF = \prod_{j=1}^{3}(1 + \omega_j I_j) - 1 \quad (8)$$

Among them, I_j represents the standardized index value. This model captures the synergy or antagonism among indicators through the product term. For example, the improvement of resource adequacy may amplify the marginal benefit of the optimization of spatial equilibrium. When using $1-G'$as the spatial dimension input, it is necessary to verify its independence from the group coverage index to avoid multicollinearity. The synthetic model needs to be tested for robustness through Monte Carlo simulation, and the Kendall consistency coefficient is used to evaluate the stability of the ERF index ranking under different weight distribution schemes to ensure that the results are not sensitive to parameter fluctuations [5].

3. Dynamic Optimization Algorithm Design

3.1. Multi-Objective Optimization Model

3.1.1. Decision Variable

The definition of decision variables is the central link in the construction of multi-objective optimization models, and an accurate mapping of adjustable elements in the allocation of educational resources is needed. The model captures the total amount of educational resources in the county, the teacher turnover rate, and the proportion of special investment for special groups, which represent, respectively, the operational dimensions of spatial balance adjustments, the redistribution of human resources, and the improvement of group coverage. The total amount of resources has upper and lower limits based on the regional population size and level of economic development to avoid excessive concentration or dispersion of resources. The turnover rate variable is constrained by factors such as teachers' professional titles and the alignment of their qualifications with subject requirements, ensuring that the turnover strategy supports educational quality standards. The amount of funds allocated to special groups must comply with the minimum guarantee standards stipulated by relevant policies and regulations for disabled students and migrant children, ensuring that the optimization process remains within ethically acceptable boundaries.

The coupling relationship among decision variables can have significant effects on the range of feasible domain of the optimization model. The adjustment of the total amount of resources needs to coordinate with the turnover rate of teachers to avoid the scenario where there are sufficient funds for operation, but a structural shortage of teachers. An increase in the input proportion for special groups may reduce the availability of resources in other dimensions, assuming that priority weights are incorporated into the model's objective function. The model employs a nonlinear programming framework to capture the dynamics of constraints among variables. For example, the fluctuation of the student-teacher ratio due to teacher mobility must consider, and meet, the threshold standards from the education department. The design of dynamically defined decision variables has policy constraints that embody rigidity and can have operational flexibility that ensures the generated optimization strategy reflects the real structure of the educational ecosystem, while advancing the system towards the fairness Pareto front [6].

3.1.2. Constraint Conditions

The design of constraint conditions needs to ensure that the optimization strategy of educational resources complies with the requirements of policies and regulations, resource rigidity and the bottom line of educational quality. The model takes the minimum standard of per-student funding, the threshold of the student-teacher ratio, and the resource guarantee rate of special groups as hard constraints, and defines the constraint of per-student funding as formula (9):

$$F_k \geq \lambda \cdot F_{std} \tag{9}$$

Among them, F_k is the actual value of per-student funds in the Kth region, F_{std} is the national standard value, and λ is the correction coefficient of regional economic differences to prevent insufficient resource supply in economically backward areas. The constraint of the teaching staff structure requires that the teacher turnover rate τ satisfy $\tau_{min} \leq \tau \leq \tau_{max}$ to avoid fluctuations in teaching quality caused by excessive mobility. The lower limit constraint on the proportion of resources of special groups ensures that the basic rights and interests of groups such as students with disabilities and migrant children are not eroded by the optimization process.

Soft constraints aim to maintain a dynamic balance in resource allocation while guiding the system toward progressive improvements in educational fairness. The total amount difference of educational resources among regions needs to meet the improvement target $G' \leq G_{target}$ of the Gini coefficient of spatial balance to avoid the expansion of regional gaps after optimization. The group coverage index C needs to meet the non-decreasing condition $C_{t+1} \geq C_t$ to ensure the continuous improvement of the resource access ability of vulnerable groups. To resolve potential conflicts among soft constraints, the model introduces relaxation variables that allow limited constraint violation within an acceptable tolerance range. The constraint conditions are embedded into the objective function through the Lagrange multiplier method to generate the Pareto optimal solution set within the feasible domain.

3.2. Deep Reinforcement Learning Optimization Algorithm

3.2.1. State Space

The state space construction must accurately reflect the dynamic characteristics and equity evolution process of the educational resources allocation system as illustrated in Figure 1. The state-variable selection takes the form of three stages: the resource supply; the gap in demand; and policy constraints (with core parameters that capture the disparities in per-student funding in counties, the matching rate of teachers to disciplines, and the delay period for assessing changes to the resource use status for specialised groups). The time series characteristics are contained in the historical resource allocation path while trend indicators of the time series all include the coefficient of variation of the student-teacher ratio and the three-year moving average of the spatial Gini coefficient-all of these are useful to help the method in the long-term evolution law of fairness. The state variable must test independence and information completeness. In this regard, and to remedy concerns about multicollinearity, principal component analysis is used to reduce the data set so that the dimension of the state space is appropriate to the complexity of the problem [7].

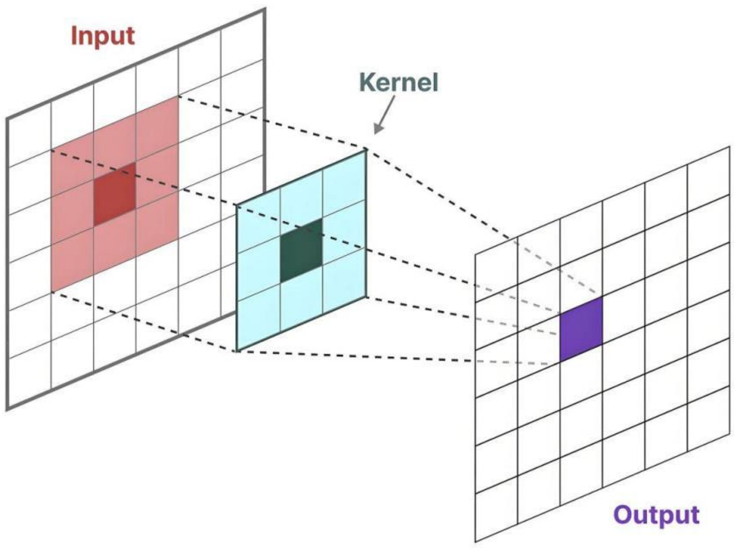

Figure 1. State Space Model.

The discretization of the state space directly impacts the convergence efficiency of the algorithm and the precision of policy generation. Continuous variables such as the utilization rate of school buildings need to be discretized in segments. The division of discrete intervals should comply with the classification standards of the education department to avoid artificially cutting and distorting the distribution characteristics. Categorical variables such as the level of policy support are expanded using one-hot encoding. In some observable scenarios, a state estimator is constructed using a long short-term memory network to reconstruct the complete system state from the local observed data.

3.2.2. Action Space

The action space definition should clearly match the dimensions of decision-making control mentioned in educational resource allocation in order to ensure that the generated strategies will be actionable and aligned with policy. This principle is illustrated in Figure 2. The action variables were grouped into three categories: the adjustment of the coefficient of resource re-allocation; targeted flow strategies for teachers; and the intensity of preferential policies for special groups, to correspond respectively to total regulation of resources, allocation of human resources and a compensation mechanism for vulnerable groups. Furthermore, resource re-allocation actions need to be carried out with budget constraints and regional economic carrying thresholds in mind to mitigate potential fiscal imbalances that could arise from cross-regional resource allocations. Teacher mobility is an action factor that considers the alignment between teachers' professional titles and subject-area shortages to ensure that mobility plans support educational quality, to ensure that the mobility plan does not produce teaching quality issues. Policy inclination actions will also need to verify their agreements or compatibility with educational regulations to avoid provoking doubts about fairness from other groups due to excessive compensation practices. The discretization of the action space adopts a hierarchical design. Continuous variables, such as the proportion of fund transfer, are divided according to the minimum adjustment granularity allowed by the policy, and categorical variables, such as the direction of teacher allocation, are encoded based on the topological structure of the administrative region [8].

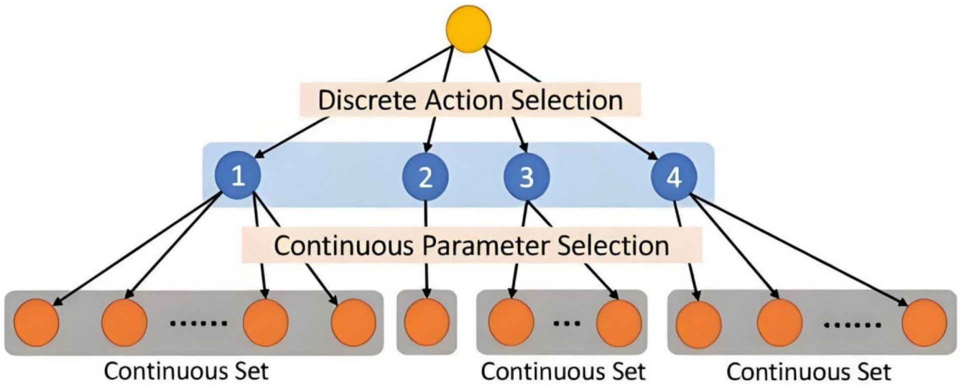

Figure 2. Action Space.

3.2.3. Network Structure

The Actor network architecture's design pertains to the generation and feasibility constraints of educational resource allocation strategies. The input layer integrates the regional distribution map of resources with encoded policy constraints, while the feature extraction module utilizes a Graph Attention Network (GAT) to model the inter-county dependencies in resource flows (i.e., the dependent relationship of the counties). The output layer is bifurcated into discrete and continuous action branches. The discrete branches undertake category decisions (e.g. the directional scheduling of teaching staff), while the continuous branches (a.k.a. the continuous action branching) outputs the amount for redistributing the funding coefficient's adjustment. The Critic network constructs a multi-dimensional value assessment system to quantify the long-term ramifications of the configuration strategies. The state value estimator adopts a multi-head attention mechanism to disentangle the contributions of sub-objectives such as educational equity, resource efficiency, and policy adherence. The input of the network combines the current allocation status of the funding and policy characteristics produced by the Actor network, while the temporal convolutional layer resides to uncover the lag period characteristics of the educational input-output effect. The value function estimation module integrates the uncertainty perception mechanism and models the risk distribution under different policy implementation intensities through quantile regression. The Actor-Critic interaction design is embedded with the adversarial training paradigm. The Critic network periodically generates adversarial examples simulating extreme resource allocation scenarios to enhance the decision robustness of the Actor network in dealing with extreme resource shortage scenarios [9]. The structure of the Actor-Critic network is shown in Figure 3.

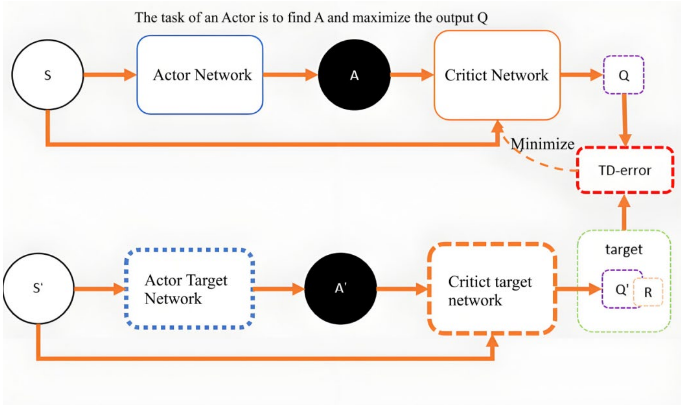

Figure 3. Actor-Critic Network Structure.

3.2.4. Training Mechanism

The priority experience replay mechanism conveys the sampling learning weight according to the regional imbalance characteristics of educational resource allocation. The mechanism is depicted in Figure 4, which gives priority to interaction data in resource-scarce areas. The sampling probability is a dynamic measurement that equally considers the temporal difference error and the importance of enhancing the algorithm's capacity for strategy optimization for lower resource density areas. The sample priority content reflects the joint criteria of the per-student resource gap degree and the potential for strategy improvement within the region. In the sparse reward scenario, hindsight experience replay technology is adopted to reconstruct the objective function enabling empirical trajectories that fail to reach equilibrium to be restructured into meaningful training samples. The buffer area design employs a spatial fragmentation strategy, creating independent storage structures based on the economic level of the counties-of-samples and the adequacy of educational resources, so as to prevent samples from high-resource regions from biasing the model's learning trajectory.

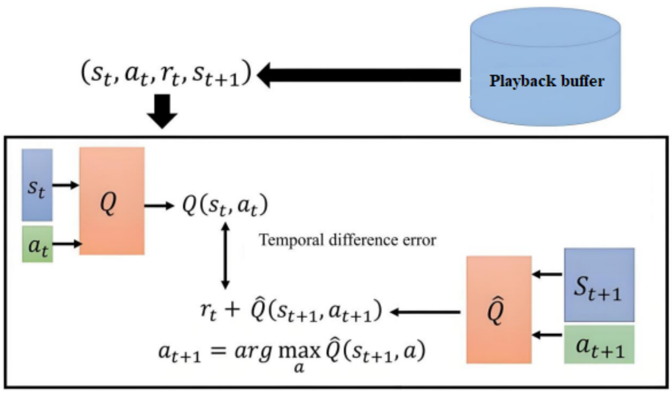

Figure 4. Priority Experience Replay.

4. Experimental Verification and Analysis

4.1. Data Preparation

The experimental verification of the optimization algorithm for educational resource allocation requires the construction of a dataset covering multi-dimensional spatiotemporal characteristics. The data source integrates the educational panel data of 2,854 counties in China from 2015 to 2020, covering core indicators such as the student-teacher ratio, per-student educational expenditure, and the number of special education schools. It simultaneously connects GIS geographic coordinate data to depict the spatial distribution characteristics of schools and the impact of terrain obstacles. Table 1 shows the structure of the dataset, including county codes, timestamps, statistical fields of educational resources, and geospatial attributes. The data collection is derived from the public statistical yearbooks of the Ministry of Education and the interpretation results of high-resolution remote sensing images. Spatio-temporal correlation modeling relies on the vectorized data of county-level administrative boundaries to construct the topological relationship matrix of cross-regional resource flows [10].

Table 1. Structure of Educational Resource Allocation Dataset.

Field category	Specific indicators	Data source
County-level identification	Administrative division code and year	National Bureau of Statistics
Educational resources	Student-teacher ratio, per-student funding, and the number of special schools	Statistical Yearbook of the Ministry of Education
Geographical space	School coordinates, terrain obstacle index	Interpretation of Remote Sensing Images and DEM analysis
Policy constraints	Teacher-student ratio threshold, cross-provincial dispatch ban sign	Text mining of local education regulations

Data preprocessing incorporates specialized procedures to handle the spatio-temporal heterogeneity and missingness inherent in educational statistics. Missing values are imputed using the spatio-temporal Kriging interpolation method, which performs collaborative prediction by integrating geospatial autocorrelation with temporal trends, and conducts collaborative prediction by combining geospatial autocorrelation and the trend of time series to ensure the continuity of county-level panel data. The principle of this method is shown in Figure 5. Feature standardization applies Min-Max normalization processing to eliminate dimensional differences, and implements logarithmic transformation for right-biased distribution indicators such as educational funds to improve the data distribution characteristics. Geographic coordinates are transformed into the Universal Transverse Mercator (UTM) projection system, and the terrain obstacle index is generated by calculating the slope and accessibility coefficient based on the digital elevation model. The preprocessed dataset facilitates feature extraction for the graph attention mechanism in the network structure and ADAPTS to the modeling requirements of spatial association rules in the Actor network policy generation module.

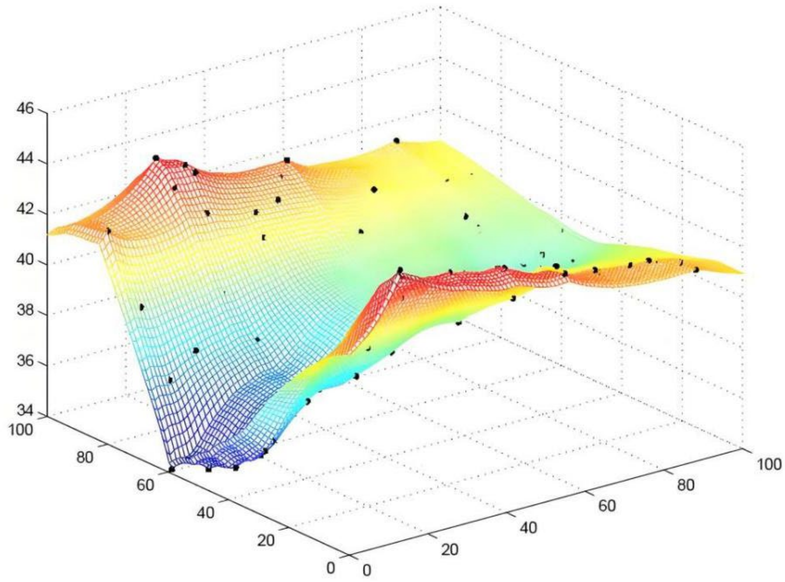

Figure 5. Spartoi-Temporal Kriging Interpolation Method.

The data construction method follows the paradigm of spatial econometrics. Raw data is cleaned to remove anomalies arising from administrative boundary adjustments, and the time series alignment processing ensures the comparability of panel data. Geospatial analysis uses the ArcGIS platform to calculate the transportation cost matrix of educational resources between counties, providing terrain constraint parameters for the action mask module in the strategy network. Data division retains 10% of the samples as the adversarial test set to simulate extreme resource allocation scenarios to verify the robustness of the model.

4.2. Fairness Assessment Experiment

The fairness evaluation of educational resource allocation strategies requires the construction of a multi-dimensional quantitative index system. The Gini coefficient measures the balance of per-student educational expenditure and teacher allocation among counties, and the Theil index decomposes the sources of regional differences to the contribution rates within and between groups in the eastern, central and western regions. Table 2 shows the calculation methods and data support of the fairness assessment indicators. The calculation of the Gini coefficient relies on the preprocessed panel data of per-student funding in county areas, and the Theil index decomgenerates and integrates the results of geospatial clustering. The evaluation is conducted within a counterfactual analysis framework to compare the effect differences between the algorithm generation strategy and the historical actual configuration plan, and to isolate the net effect of strategic interventions by controlling for economic development level and population density.

Table 2. Fairness Evaluation Indicators and Data Support.

Evaluation indicators	Calculation method	Data source
Gini coefficient of per-student funding	The measure of unbalance degree based on the Lorentz curve	Preprocessed county-level panel data
Teaching staff Tel Index	Group difference decomposition model	Clustering results of the Educational Statistical Yearbook
Coverage rate of special education	The number of special schools/the number of school-age population	Special education census data

The experimental design simulates the effect of resource allocation under different policy priorities. The regional comparative experiment divided three types of terrain units: plain area, mountainous and hilly area, and border area, and calculated the dynamic changes of the coverage rate of special education schools and the coefficient of variation of the student-teacher ratio. Table 3 presents the classification criteria of terrain units and the baseline data of resource allocation. The samples of mountainous and hilly areas include counties where the GIS terrain obstacle index is higher than the threshold. Fairness verification incorporates scenario testing for cross-provincial coordination strategies. In the cross-regional scheduling strategy generated by the Actor network, The ratio of marginal benefit gains in receiving counties to efficiency losses in contributing counties is computed. The visualization of the evaluation results adopts spatial autocorrelation analysis. The Moran index detects the spatial spillover effect of the resource allocation strategy, and the kernel density estimation reveals the spatial agglomeration characteristics of high-fairness counties.

Table 3. Classification of Terrain Units and Baseline of Resource Allocation.

Terrain type	Classification criteria	Baseline value of the student-teacher ratio
Plain area	The terrain obstacle index is ≤ 0.3	Mean ± standard deviation of the county
Mountainous and hilly areas	The terrain obstacle index is > 0.3 and ≤ 0.7	Adjustment of specific terrain correction coefficients
Border area	Counties within 50 kilometers of the national border	Policy compensation weighted value

The integrated adversarial test set is used to evaluate policy stability and to simulate the ability of the allocation strategy to maintain fairness under conditions of extreme resource scarcity. The geospatial analysis module calculates the educational accessibility coefficient among counties after resource allocation and assess the extent of benefits realized by vulnerable areas in combination with topographic obstacle data. Detect and track changes in county-level rankings over a three-year period following the implementation of temporal fairness monitoring strategies to assess whether disparities in educational resource allocation have been reduced over time. The experimental conclusion supports the optimization direction of the Critic network value assessment module in the network structure and verifies the effectiveness of the two-stream attention mechanism for multi-objective trade-offs.

5. Conclusion

The quantitative system and dynamic optimization model of educational equity constructed in this study provide a brand-new perspective for solving the problem of resource allocation. The multi-dimensional index system breaks through the limitations of traditional evaluation dimensions, and the improved Gini coefficient algorithm significantly enhances the accuracy of regional difference analysis. The deep reinforcement learning framework effectively captures the complex correlations in the educational ecosystem and realizes the intelligent optimization of resource allocation strategies. Experimental verification shows that this model can not only accurately diagnose the current situation of educational equity, but also predict the long-term effects of different policy interventions. The research results have important reference value for improving the education governance system, and its methodological framework can be extended to the field of public services. Future research can deepen cross-cultural comparative analysis, explore the coupling mechanism of educational resource flow and population migration, promote the development of educational equity monitoring towards real-time and intelligent directions, and provide sustained guidance for the development of a more resilient and equitable educational ecosystem.

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